MODEL-PREDICTIVE CONTROL FOR STEAM USAGE OPTIMIZATION IN A CONTINUOUS EVAPORATOR

163001022

Abstract: *This project outlines a model predictive control (MPC) solution for a continuous evaporator. Nowadays energy consumption has a significant impact in the finished goods unit costs. Based on that, the goal is to optimize the steam usage in a manufacturing chemical plant and consequently reduce utilities supply variable cost. The key equipment in the process is the evaporator. This equipment is operated in a continuous mode and the upstream equipments in a batch mode. The evaporator motive steam is manually controlled by the operators, according to their personnel experience. Upstream process variations are not properly corrected by the operators, which causes unbalance between the amount of boiling water and motive steam in the evaporator. MPC concept is based on constraint, disturbance, controlled and manipulated variables which establish the optimization process control strategy. To build the model it was used Delta-V function blocks which were available in the Distributed Control System (DCS). Constraint variables must be configured to avoid impacts in safety, quality and equipment reliability. Disturbance variables have a direct gain associated with the controlled variable. The manipulated variable is tuned to assure low process variability. For this particular case, the constraint variable is the evaporator concentration which is important to guarantee the product quality. No disturbance variable was used in the modeling due to low statistical correlation between the potential ones. According to the process characteristics, it was used the 30 minutes moving average of the evaporator feed tank level indicator as the controlled variable. The model prediction considers the steam flow-rate set point minimization when the controlled variable is lower than 55%. Otherwise it increases the steam flow-rate set point. The implementation replaced the experienced operator's curve by an optimized auto-adjusted one. The key factor for the success of this project was the modeling strategy adopted that considered the plant in steady state mode in order to avoid external influences. It assured high process reproducibility and repeatability. The project accomplished the goals, improving the steam consumption, reducing energy costs and saving money. Besides that, this automation technology has been demonstrating its importance for process control variability minimization aligned with environmental efforts to save natural resources.*

Keywords: *Model-predictive control. Cost savings. Natural resources minimization.*

1. INTRODUCTION

Predictive process control involves the ability to monitor and control a continuous materials process in real time. This allows the conditions of the process to be adjusted quickly and responsively, and avoids the delay associated with only monitoring the final product. The potential of this technology sub-area is great, as it can improve the yields and productivity of a wide range of industrial processes. It can also contribute to the reduction in unwanted or polluting side processes.

Advancing the state of the art in predictive process control requires advances in sensor capability, in data communications and data processing, and in modeling. Improved interfaces with operators, usually via graphic displays, will also provide improved control system performance. The most important class of sensors for this sub-area is non-imaging sensors which can be used to measure a vast range of phenomenology such as temperature, pressure, humidity, radiation, voltage, current, or presence of a particular chemical or biological material. Specialized micro sensors can be used to detect particular chemical or biological agents. The information generated by the sensors must be combined and processed using data processing and models specific to the process being monitored.

Model Predictive Control (MPC) is widely adopted in industry as an effective means to deal with large multivariable constrained control problems. The United States is a major player in all of the technologies which make up predictive process control, followed by Germany, Japan and UK.

The main idea of MPC is to choose the control action by repeatedly solving on line an optimal control problem. This aims at minimizing a performance criterion over a future horizon, possibly subject to constraints on the manipulated inputs and outputs, where the future behavior is computed according to a model of the plant, as showed in figure2. Issues arise for guaranteeing closed-loop stability, to handle model uncertainty, and to reduce on-line computations, according to (Bemporad et al., 1997).

MPC is an advanced method of process control that has also been in use in the process industries such as chemical plants and oil refineries since the 1980s. Model predictive controllers rely on dynamic models of the process, most often linear empirical models obtained by system identification. The models are used to predict the behavior of dependent variables (outputs) of a dynamical system with respect to changes in the process independent variables (inputs). In chemical processes, independent variables are most often set points of regulatory controllers like flow, temperature or pressure control loops, while dependent variables are most often constraints in the process like product concentration, pH, moisture, etc. The model predictive controller uses the models and current plant measurements to calculate future moves in the independent variables that will result in operation that honors all independent and dependent variable constraints. The MPC then sends this set of independent variable moves to the corresponding regulatory controller set points to be implemented in the process, (Patwardhan et al., 1990).

Despite the fact that most real processes are approximately linear within only a limited operating window, linear MPC approaches are used in the majority of applications with the feedback mechanism of the MPC compensating for prediction errors due to structural mismatch between the model and the plant. In model predictive controllers that consist only of linear models, the superposition principle of linear algebra enables the effect of changes in multiple independent variables to be added together to predict the response of the dependent variables. This simplifies the control problem to a series of direct matrix algebra calculations that are fast and robust, according to (Garcia et al., 1989).

2. BASELINE PROCESS

This project outlines a model predictive control (MPC) solution for a continuous evaporator. Nowadays energy consumption has a significant impact in the finished goods unit costs. Based on that, the goal is to optimize the steam usage in a manufacturing chemical plant in 5% and consequently reduce utilities supply variable cost. The key equipment in the process is the evaporator, in which is operated in a continuous mode and the upstream equipments in a batch mode that can difficult the application. The evaporator motive steam is manually controlled by the operators, according to their personnel experience. Upstream process variations are not properly corrected by them, which causes unbalance between the amount of boiling water and motive steam in the evaporator.

Monsanto has been using MPC concepts in order to improve process outputs and reduce manufacturing costs. In order to implement a reliable operation, two industrial computers were installed, being one used as server and the other used for engineering, as seen in Fig. (1).

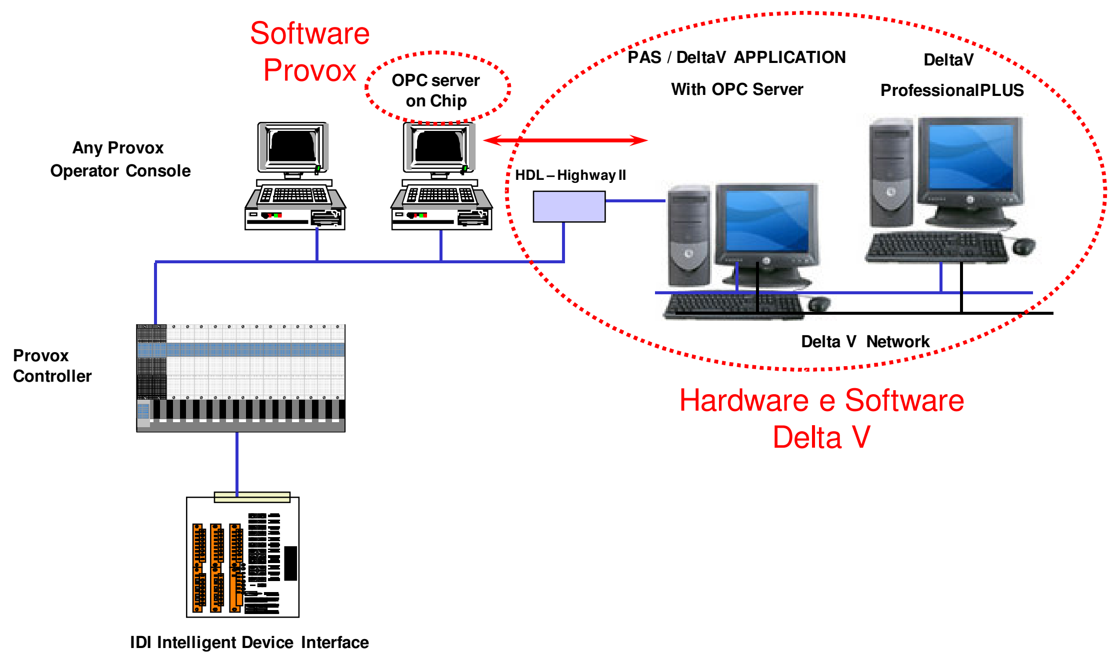

Figure 1. MPC network architecture

A benchmarking was done to find out potential software to be used for implementing MPC applications. After a market search and considering the restrictions of the existing plant facilities, technical aspects and system's compatibility, DeltaV system was defined to be the platform to run MPC applications, (Emerson, 2006)**.**

This system was connected to the existing Provox SDCD system throughout OPC mirror software and a high data link communication drive. The model-predictive control was configured in the Delta V environment, using available MPC function blocks. Heart bit was implemented for checking the network operability and guarantee a safe operation. In case the network is out of service, the MPC mode is changed from auto to manual and the control loops associated are changed from remote set point to auto mode, allowing the operators to modify the controller's set points and get the plant control.

3. PROJECT IMPLEMENTATION

MPC concept is based on constraint, disturbance, controlled and manipulated variables which establish the optimization process control strategy. To build the model it was used Delta-V function blocks which were available in the Distributed Control System (DCS). Constraint variables must be configured to avoid impacts in safety, quality and equipment reliability. Disturbance variables have a direct gain associated with the controlled variable. The manipulated variable is tuned to assure low process variability. To establish the process control strategy for MPC it was considered the following variables:

- Constraint variable: product concetration in the continuous evaporator.
- Disturbance variables: not used.
- Controlled variable: 30 minutes moving average of the evaporator feed tank level.
- Manipulated variable: steam feed rate in the evaporator thermocompressor.

For this particular case, the constraint variable is the evaporator concentration which is important to guarantee the product quality. No disturbance variable was used in the modeling due to low statistical correlation between the potential ones. According to the process characteristics, it was used the 30 minutes moving average of the evaporator feed tank level indicator as the controlled variable. The model prediction considers the steam flow-rate set point minimization when the controlled variable is lower than 55%. Otherwise it increases the steam flow-rate set point. The implementation replaced the experienced operator's curve by an optimized auto-adjusted one. The control strategy is shown in the Fig. (2).

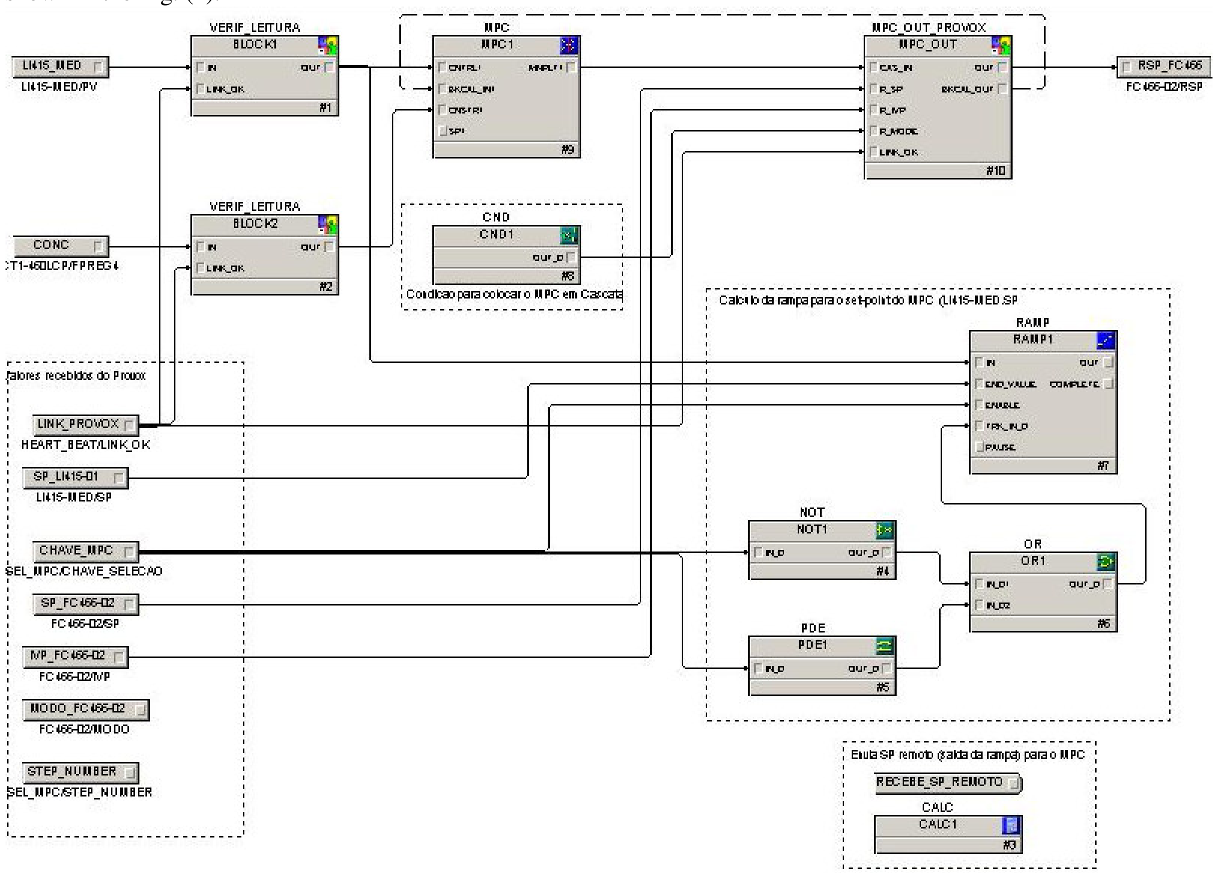

Figure 2. MPC control blocks

The first step of modeling was the identification of all potential variables in the continuous evaporator that could take part of the predictive model. The preliminary evaluation indicated no needs for disturbance variable, due to low correlation of the evaporator temperature and pressure.

The next step consisted in some plant runs in order to define the gain associated with the controlled, constraint and manipulated variables. For a properly modeling, the evaporator was running in steady state mode and in full capacity. Manual steps were applied in the steam flow rate control loop and simultaneously the Delta V predict software collected the data from the controlled, constraint and manipulated variables in order to calculate gains and dead times, as shown in Fig. (3). Those parameters were checked by doing some manual calculation according to the physical section areas of the evaporator feed tank and the evaporator body. The numbers were very similar to those ones calculated by software.

Then, the model parameters were downloaded to MPC controller in the Delta V application station. After that, some plant trials were done in order to confirm the effectiveness and reliability of the model results. To avoid boiler operation upsets in the utilities area, it was defined a safe rate of 200 (kg/hr)/min for the MPC controller to ramp down and up the steam flow rate set points. The set point rate limit represents 1% of the engineering range for the steam control feed valve.

The MPC operation is selected by the operators throughout a switch configured in the Provox (SDCD) operating faceplate. When MPC is chosen, the steam feed control loop is changed automatically from auto to remote set point mode. For troubleshooting, the last steam flow rate set point is frozen, the control loop mode returns to auto and an alarm is activated.

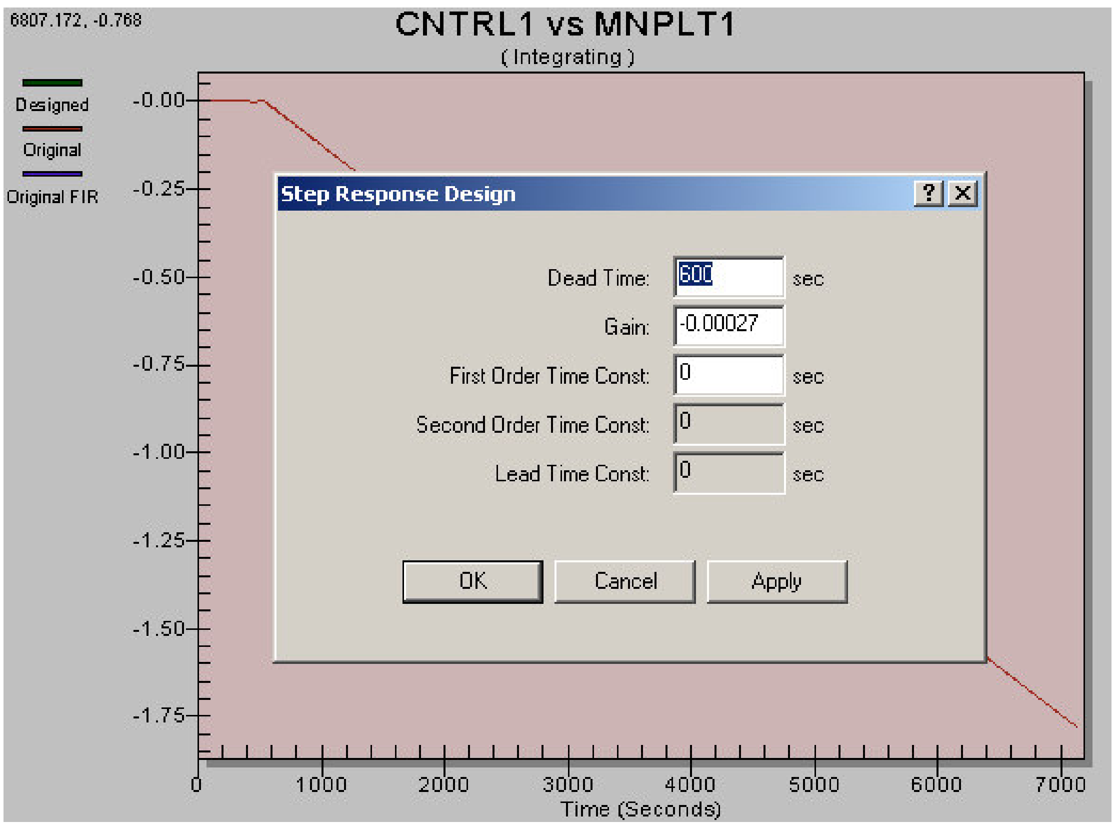

Figure 3. Model-predictive control parameters

4. RESULTS AND DISCUSSION

This project minimized water addition in the continuous evaporator in order to compensate mass unbalances, reducing the evaporator concentration variability and bringing significant savings with low capital investment for the company. Another important result was the minimization of natural resources like natural gas and well water used as raw materials in the boiler to produce steam. The steam consumption was reduced in 7.5%, debottlenecking the equivalent of 28 operating days/year the boilers capacity. MINITAB® software was used for calculating the indexes and supports the technical evaluation. According to (Hayashi, 2005), two sample-T analyses were applied, demonstrating a significant statistical improvement in the steam usage when comparing the baseline and improve phases, as seen in Fig. (4).

In general, the most important part of the modeling process is to perform the plant tests in steady state regime, eliminate outliers and avoid manual interferences. Planning, implementation strategy, and process knowledge are fundamental to guarantee the model accuracy at long term. The configuration itself is very simple but confirmation runs are required to evaluate the predictive model effectiveness and reliability and make sure that the expected results are going to be accomplished. Tracking the model performance and training people are essential for continuous improvement. Engineering configuration access restriction is another important factor to avoid unexpected changes in the controller parameters with consequent accuracy losses. Troubleshooting strategy planning should be considered to prevent safety issues and avoid operator's mistake.

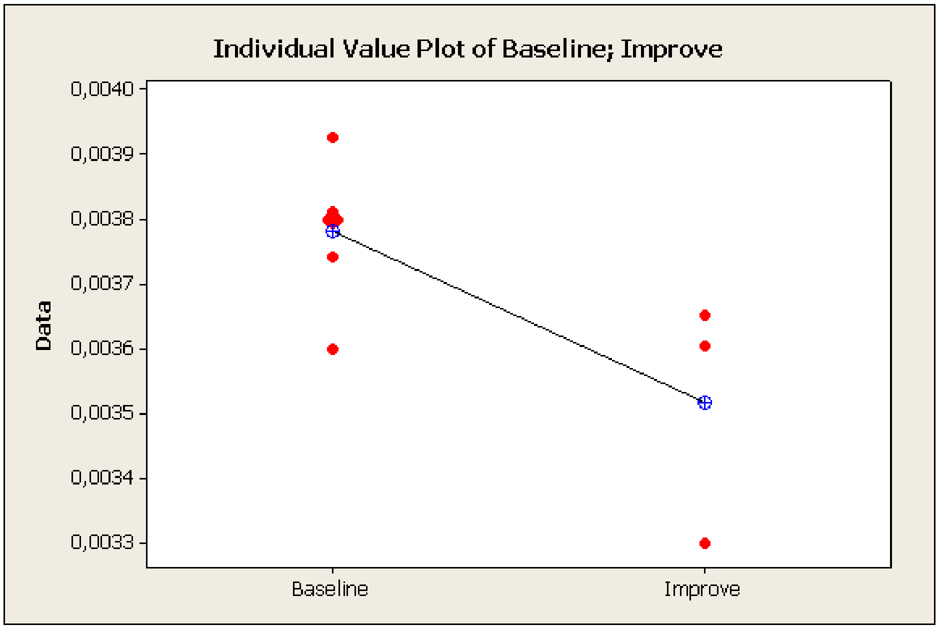

Figure 4. Steam usage reduction

5. CONCLUSIONS

The project was implemented accomplishing the goals and was recognized as a breakthrough solution. Technology innovation and business strategies were focused on this project by searching modern ways for manufacturing process control and management. Smart tools, new control strategies, process modeling and teamwork were very important to achieve success in this implementation. The engineering approach in this work allowed the process to be anticipated avoiding waste of resources in the manufacturing organization and working in a proactive vision. The technology innovation provided a friendly user tool for the operators and knowledge exchange among the team. Another key factor for the success of this project was the modeling strategy adopted that considered the plant in steady state mode in order to avoid external influences. It assured high process reproducibility and repeatability, improving steam consumption, reducing energy costs and saving money. Besides that, this automation technology has been demonstrating its importance for process control variability minimization aligned with environmental efforts to save natural resources.

6. REFERENCES

A. Bemporad, A. Casavola, and E. Mosca, 1997. "Nonlinear control of constrained linear systems via predictive reference management", IEEE Trans. Automatic Control, vol. AC-42, no.3, pp. 340-349, viewed on April 20, 2006 <http://www.dii.unisi.it/~bemporad/mpc.html>.

Patwardhan, A.A., J.B. Rawlings, and T.F. Edgar, 1990. "Nonlinear model predictive control".

Garcia, Prett, Morari, 1989, "Model predictive control: theory and practice", Automatica, 25, pp.335-348.

EMERSON Process Management Company, viewed on April 19, 2006 <http://www.emersonprocess.com/education/catalogrev/ automationsystems/7202.asp> and <http://www.emersonprocessxperts.com/ archives/analyzers/>.

Hayashi, J. Six Sigma Training, 2005, "First week chapter 5", issue 5, pg. 3 – 78.

7. RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.